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AUTHOR	Burdenski, Thomas K., Jr.
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ABSTRACT

This paper discusses the importance of interpreting both regression coefficients and structure coefficients when analyzing the results of multiple regression analysis, particularly with correlated predictor variables. The concepts of multicolinearity and suppressor effects are introduced, along with examples from the previously published articles that demonstrate how erroneous conclusions are drawn when researchers fail to consult both beta weights and structure coefficients (or both beta weights and zero-order correlations). (Contains 4 tables, 1 figure, and 39 references.) (Author/SLD)

Running head: STRUCTURE COEFFICIENTS

The Importance of Structure Coefficients in Multiple Regression: A Review with Examples from Published Literature

Thomas K. Burdenski, Jr.

Texas A&M University 77843-4225

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Abstract

The present paper discusses the importance of interpreting <u>both</u> regression coefficients and structure coefficients when analyzing the results of multiple regression analysis, particularly with correlated predictor variables. The concepts of multicollinearity and suppressor effects are introduced, along with examples from the previously published articles that demonstrate how erroneous conclusions are drawn when researchers fail to consult both beta weights and structure coefficients (or both beta weights and zero-order correlations).

Roughly a dozen years ago, Jacob Cohen (1988), a preeminent author, critic, and research methodologist in the behavioral sciences, declared that:

> During the past decade, under the impetus of the computer revolution and increasing sophistication in statistics and research design among behavioral scientists, multiple regression and correlation analysis (MRC) has come to be understood as an exceedingly flexible data analytic procedure remarkably suited to the variety and types of problems encountered in behavioral research. (p. 407)

Fifteen years earlier, Kerlinger and Pedhazur (1973) enthusiastically endorsed multiple regression:

> It is a powerful analytic tool widely applicable to many different kinds of research problems. It can be used effectively in sociological, psychological, economic, political, and educational research. It can handle continuous and categorical variables. In principle, the analysis is the same. Finally, as we will abundantly show, multiple regression can do anything the analysis of variance does--sums of squares, mean squares, F ratios--and more. (pp. 2-3)

Unlike ANOVA, there are no constraints on the types of independent variables one can employ when utilizing multiple regression. Regression can be used when the predictor variables are correlated or uncorrelated, continuous or nominal.

Given the prominent role that regression should and does have in the behavioral sciences (cf. Elmore & Woehlke, 1988; Willson, 1980), the purpose of the present paper is to argue the importance of interpreting <u>both</u> regression coefficients and structure coefficients when analyzing the results from multiple regression analysis, particularly with correlated predictor variables. First, the General Linear Model (GLM) is introduced as a framework for the remaining discussion. Second, the bivariate and the multiple regression model is introduced. Third, the use structure coefficients as an interpretation aid is described.

Fourth, the relative interpretive values of beta weights and structure coefficients are explored. Fifth, a case is made that both sets of coefficients usually must be interpreted (Heidgerken, 1999). Finally, published examples of both correct and incorrect interpretations of regression results, based on what coefficients were interpreted, are cited.

The General Linear Model (GLM)

Three Levels of the General Linear Model

Multiple regression is related to all other parametric analyses via the General Linear Model (GLM) (Baggaley, 1981). Cohen (1968) noted that while linear multiple <u>regression</u> analysis subsumes all univariate parametric methods (e.g., *t* test, ANOVA, ANCOVA, *r*) as special cases, multiple regression has practical advantages:

> The practical advantages of MR (multiple regression)

> ...will be seen to constitute a very flexible general system for the analysis of data in the most frequently arising circumstance, namely, where an interval scaled or dichotomous (dependent) variable is to be "understood" in terms of other (independent) variables, however scaled. (p. 427)

Knapp (1978) extended Cohen's arguments by showing that all common parametric tests of statistical significance (all the parametric univariate methods, the chi-square test of independence of two variables, and MANOVA, MANCOVA, and descriptive discriminant analysis [Huberty, 1994]) can all be treated as special cases of canonical correlation analysis, which is the general procedure for investigating the relationships between two sets of variables. Then Bagozzi, Fornell, and Larcker (1981) noted that all univariate and multivariate statistical methods are subsumed by the most general case of the General Linear Model: structural equation modeling (SEM), which has more utility in direct theory testing than canonical correlation analysis, and also directly incorporates measurement integrity as part of estimation (Thompson, in press).

Specifically, canonical correlation analysis cannot determine the statistical significance of individual parameter estimates or relax selective assumptions of the canonical model based on theory or observed data. SEM is a more flexible tool for data analysis and the problem of determining statistical significance of each parameter estimate is overcome by using estimated standard errors to calculate "critical ratios" (or t's) for the evaluation of individual weights and covariances.

Weights as a Common Feature of all GLM Methods

One aspect of the General Linear Model is that all classical univariate and multivariate tests share in common the application of weights to the measured/observed variables to estimate each person's score on each synthetic/latent variable.

> As conventional parametric methods are all correlational least square analyses, all such analyses involve weights similar to the beta weights generated in regression. These weights are all analogous, but are given different names in different analyses (beta weights in regression, pattern coefficients in factor analysis, discriminant functions coefficients in discriminant analysis), mainly to obfuscate the commonalities of all parametric methods, and to confuse graduate students. (Thompson, 1992a, pp. 906-907)

In regression in particular, the independent or predictor variables are differentially weighted using "unstandardized weights" or "standardized weights" so that the correlation between the composite scores thus obtained and the measured dependent variable, or the criterion, is maximized (Pedhazur, 1997). Using the regression equation and scores on the independent variables, one can calculate each person's score on the latent composite variable.

When the multiplicative weights are applied to the predictor variables converted to standard score form, the "standardized" weights are called beta (β) weights. [In actuality, the weights as multiplicative constants cannot be standardized, and are called this only because they are applied to the measured predictor variables themselves in standard score form.] When the weights are applied to unstandardized predictor variables, they are called "b" weights.

Multiple Correlation and Regression

Regression Weights

Bivariate linear regression using a single predictor variable "X" and a single criterion "Y" can be extended to multiple correlation and multiple linear regression (Hinkle, Wiersma & Jurs, 1998; Huberty & Petoskey, 1999). In multiple correlation, the relationship between the criterion variable "Y" and the predictor variables (X_1, X_2, ..., X_k) is determined, whereas in multiple regression, scores on the criterion variable "Y" are predicted using multiple predictors (X_1, X_2, ..., X_k). In bivariate linear regression, a straight line is fit to the scatterplot of points; the equation of this line, called the regression equation, has the form $Yhat_i = a + b(X_i)$, where $Yhat_i$ is the predicted value of the criterion variable for a given X value on the predictor variable. The regression coefficient, b, is the slope of the line, and the regression additive constant, a, is the Y axis intercept of the regression line.

In multiple linear regression, we again have a single criterion variable "Y", but we have k predictor variables (i.e., k

is greater than or equal to two). These predictor variables are combined into an equation, called the multiple regression equation, which can be used to predict scores on the criterion variable ($Yhat_i$) from scores on the predictor variables (X_i's). The general form of the equation is:

$$Yhat = b_1X_1 + b_2X_2 + \ldots b_kX_k + a,$$

where the b's are the "unstandardized" regression coefficients for the respective predictor variables and a is the regression additive constant. Note that in the two predictor variable case, for example, when X_1 and X_2 are both equal to 0, or if both b weights equal zero, the related $Yhat_i$ score equals the a weight.

Unfortunately, the b weights are jointly sensitive to (a) the correlation of each predictor with Y, (b) the correlations among the predictor variables, and (c) the variability of predictor variables in relation to the dependent variable Y. Each of these conditions create problems when interpreting b weights, because the weights are confounded by these various influences. That is, several measured predictor variables might all have b weights of +2.0, but the weights might be due to very different combinations of these three influences. This makes difficult or impossible the interpretation of regression results based solely on examination of "unstandardized" weights.

To resolve these difficulties, "standardized" regression coefficients are usually computed to facilitate comparisons across variables with different standard deviations, scales, or metrics. The beta weights are computed using the formula:

$$\text{beta} = b\ (SD_X\ /\ SD_Y).$$

The b and beta weights will be equal when (a) either is zero or (b) the standard deviations of both variables are equal (Thompson, 1992b).

According to Cooley and Lohnes (1971), some researchers judge the relative contributions of the predictors in the regression equation based on the magnitudes of their respective beta weights. They also pointed out a serious drawback to relying on beta weights to interpret regression results:

> Our tendency to de-emphasize the beta weights stems from experience with the phenomenon of extreme fluctuation of regression weights from sample to sample when the sample size is small. Even when the sample size is moderate, there is substantial fluctuation. (p. 55)

The unwary researcher might be tempted to regard the predictor variable having the beta weight with the largest absolute value as the best predictor.

Most frequently, the interpretation of regression results focuses on an evaluation of the beta (β) weights because they are not affected by variances (standard deviations) in the measured variables. As a variable's beta weight deviates further from zero in either a positive or negative direction, the predictor variable is being assigned greater influence in determining the scores on the latent criterion composite variable. Conversely, as a beta weight approaches zero, the measured predictor variable is ostensibly less influential.

However, it is possible, as we shall see, for a predictor variable to have a near-zero beta weight and to still have strong predictive capability when the predictive power of that variable is arbitrarily hidden for a given data set (as in the case of multicollinearity between predictor variables). Furthermore, it is also possible for a predictor that is perfectly uncorrelated with the dependent variable and to have the largest beta weight for a given analysis. Clearly, beta weights do not tell the whole story for a given regression analysis!

Impacts of Collinearity on the Weights and Their Standard Errors

The condition of predictor variables being correlated with each other is variously called multicollinearity, collinearity, or ill conditioning. Belsley, Kuh, and Welsch (1980) noted that multicollinearity presents both computational and statistical problems:

> Computationally, this means that solutions to a set of least-squares normal equations (or, in general, a solution to a system of linear equations) contains a number of digits whose meaningfulness is limited by the conditioning of the data... This computational problem in the calculation of least-squares estimates may be minimized, but never removed. The intuitive distrust held by users of least squares of estimates based on ill-conditioned data is therefore justified... [because] statistically... collinearity

> causes the conditional variances [of the weights and their standard errors] to be high. (pp. 114-115)

Additional problems with high collinearity between independent variables identified by Pedhazur (1982) include: (a) imprecise estimation of regression coefficients (beta weights) because slight fluctuations due to sampling error or random error in the presence of multicollinearity may lead to very large fluctuations in the estimation of regression coefficients, and (b) even reversal of the signs of regression coefficients.

Structure Coefficients as an Alternative Interpretation Aid

Definition and Calculation

Once composite predicted scores ($Yhat_i$) are computed for all participants, the correlation between each measured independent variable and the latent/synthetic composite scores is referred to as the structure coefficient (i.e., r_s), structure correlation, or "loading". Pedhazur (1997) noted that the "squared structure coefficient indicates the proportion of variance shared by the variable with which it is associated and the vector of composite scores" (p. 898). In regression one simple alternative way of calculating structure coefficients is by using the formula:

$$r_s = r_{xy} / R,$$

where the structure coefficient for independent variable x equals the correlation between the dependent variable y and the predictor x (i.e., the zero-order correlation) divided by the multiple correlation of y with all of the independent variables as a group.

The GLM Perspective on Structure Coefficients

It is intriguing that throughout the General Linear Model the use of structure coefficients is heavily emphasized. As Thompson and Borrello (1985) noted, this reality suggests the potential importance of also interpreting structure coefficients when evaluating regression results, insofar as regression is itself a prominent member of the GLM family. In Huberty's (1994) words,

> If a researcher is convinced that the use of structure *r*'s makes sense in, say, a canonical correlation context, he or she would also advocate the use of structure *r*'s in the contexts of multiple correlation, common factor analysis, and descriptive discriminant analysis. (p. 263)

For example, as regards factor analysis, which is actually an implicit part of canonical correlation analysis and all the parametric methods subsumed by CCA (Thompson, 1984, pp. 11-16), Gorsuch (1983) emphasized that a "basic matrix for interpreting the factors is the factor structure" (p. 207, emphasis added). Similarly, as regards descriptive discriminant analysis, Huberty (1994) noted that "construct definition and structure dimension [and not hit rates] constitute the focus of a descriptive discriminant analysis" (p. 206, emphasis added).

And most researchers concur that the interpretation of structure coefficients is essential to understanding canonical results. As Meredith (1964, p. 55) suggested, "If the variables within each set are moderately intercorrelated the possibility of interpreting the canonical variates by inspection of the appropriate regression weights [function coefficients] is practically nil." Levine (1977) was even more emphatic:

> I specifically say that one <u>has</u> to do this [interpret structure coefficients] since I firmly believe as long as one wants information about the nature of the canonical correlation relationship, not merely the computation of the [synthetic function] scores, one must have the structure matrix. (p. 20, emphasis in original)

<u>Interpretive Value of Weights and Structure Coefficients</u>

<u>Standardized Weights</u>

The argument in favor of consulting standardized weights when interpreting the origins of regression effects is that these weights are used to create the composite scores actually correlated in regression. That is, the bivariate <u>r</u> between the <u>y</u> and the Yhat scores is the multiple <u>R</u>. A predictor with a multiplicative weight of zero does not affect the computation of the latent Yhat scores, and indeed is obliterated by the multiplicative constant of zero. However, there are problems associated with solely interpreting the weights.

<u>No distinct range</u>. As Thompson (1994) explained, "The beta weights in a regression analysis are the correlation coefficients between the respective predictors and the dependent variable <u>only</u> when those predictors that are correlated with the dependent variable are perfectly uncorrelated with each other" (p. 20). Thus, whenever predictors are correlated, as is often the case in

research modeling a reality in which many variables are somewhat related to each other, the beta weights do not have a distinct range. This means that the weights can only be interpreted in relation to each other within a given study.

Not Measures of Relationship. Furthermore, it is clear that when the predictors are correlated the "standardized" weights are not correlation coefficients and absolutely may not be interpreted as indices of the relationships of the predictors with the outcome variable, notwithstanding the fact that exactly this misinterpretation is frequently offered in the literature. Regression weights are influenced by the relationships of the predictor variables with *y*, but the weights as statistics do not only evaluate these relationships, and therefore cannot correctly be used as indices of relationship.

That is, a measured predictor variable with a negative relationship with *y* (and thus a negative structure coefficient) may have a negative β weight, but that same predictor may also have either a zero or a positive β weight. Conversely, a measured predictor variable with a positive relationship with *y* (and thus a positive structure coefficient) may have a positive β weight, but that same predictor may also have either a zero or a negative β weight. Finally, a predictor with a zero relationship with *y* (and thus also a zero structure coefficient) may have a zero β weight, but could also have either a positive or a negative β weight.

Context Dependence. Also, too few researchers appreciate the fact that the regression weights may change radically with the deletion or the addition of even a single predictor variable. That is, the values of the weights are highly context-dependent. As Thompson (1999b) emphasized, "Any interpretations of weights must be considered context-specific. Any change in the variables in the model can radically alter all of the weights" (p. 48, emphasis in original).

Put differently, the regression weights are correct only if all the correct predictors are employed, and only the correct predictors are employed. This means that the model is "correctly specified." Unfortunately, as Pedhazur (1982) has noted, "The rub, however, is that the true model is seldom, if ever, known" (p. 229). And as Duncan (1975) has noted, "Indeed it would require no elaborate sophistry to show that we will never have the 'right' model in any absolute sense" (p. 101).

Structure Coefficients

Cooley and Lohnes (1971) were early advocates for the interpretation of structure coefficients in regression research. Thorndike (1978) also pointed out the hazards of only interpreting beta weights when reviewing the results of multiple regression analyses:

> It might be argued that the beta weights provide the required information, but such is not the case. The beta weights give us the relative contribution of each variable to the variance of the composite, but to the extent that the X variables are correlated, the one with the larger correlation with the

> criterion will receive a large weight at the expense of the other... [and] a description in terms of the beta weights would give a false impression of the relationship. Therefore, when description of the composite of X variables is desired, it is necessary to compute the correlations of the X variables with the composite. (pp. 153-154)

Structure coefficients do have the advantage of having a distinct potential range (i.e., from -1 to +1). And consultation of these coefficients make sense, given the previous realization that R is the bivariate r of y with Yhat. That is, given R focuses on the Yhat scores, it makes sense to want to understand the underlying structure of the latent variable. As Thompson (1999a) recently noted, "the reason that structure coefficients are called 'structure' coefficients is that these coefficients provide insight regarding what is the nature or structure of the underlying synthetic variables of the actual research focus" (p. 15).

Disagreements in the Literature

However, there has not been unanimous agreement among researchers on the utility of structure coefficients. For example, Harris (1992) stated that structure coefficients can be potentially misleading and argued that they should be abandoned in favor of interpreting weights.

A somewhat different view was offered by Pedhazur (1982, p. 691), who noted that structure coefficients are "simply zero-order correlations of independent variables with the dependent variable divided by a constant, namely, the multiple correlation coefficient. Hence, the zero-order correlations provide the same information." In response, Thompson and Borrello (1985) argued that "the interpretation of only the bivariate correlations seems counter-intuitive. It appears inconsistent to first declare interest in an omnibus system of variables and then to consult values that consider the variables only two at a time" (p. 208).

However, it is clear that interpretation of either (a) beta weights and structure coefficients or (b) beta weights and the zero-order correlations of the predictors with y will both yield identical interpretations. The point is that beta weights alone should not be the basis of interpretation, except when predictors are perfectly uncorrelated, and thus each predictor's β equals its r with y.

More recently, Pedhazur (1997) argued that "because one may obtain large structure coefficients even when results [i.e., R^2] are meaningless, their use in such instances may lead to misinterpretations" (p. 899). He then presented a hypothetical data set involving an R^2 of .00041, for which the r_S for the first predictor variable is .988. Pedhazur then noted that "These are impressive coefficients, particularly the first one... But what is not apparent from an examination of these coefficients is that they were obtained from meaningless results" (p. 899).

This objection seems somewhat strange. As Thompson (1997) explained,

All analyses are part of one general linear model

> (cf. Thompson, 1991). When interpreting results in the context of this model, researchers should generally approach the analysis hierarchically, by asking two questions:
>
> --Do I have anything? (Researchers decide this question by looking at some combination of statistical significance tests, effect sizes..., and replicability evidence.)
>
> --If I have something, where do my effects originate? (Researchers often consult both the standardized weights implicit in all analyses and structure coefficients to decide this question... (p. 31)

As Pedhazur himself acknowledged (p. 899) should done as regards discriminant and canonical correlation analyses, in regression as well one would only bother to examine the structure coefficients after one has determined that the results are noteworthy. So, given this hierarchical contingency-based approach to the interpretation of GLM results, this criticism of Pedhazur (1997) seems irrelevant.

Thoughtful Resolution

As Figure 1 demonstrates, it is possible to have a predictor variable with the greatest predictive potential (X_2) lose credit to two or more other predictors (X_1 and X_3) whose predictive area overlaps that of the first predictor. The X_1 predictor may arbitrarily be given no credit for its predictive potential and could have a beta weight of zero. In such an instance, it is important to have information about the predictive potential of that variable, information that is easily gained by examining each predictor variable's structure coefficient.

Insert Figure 1 About Here.

In a dramatic example of how misleading the examination of only regression coefficients can be in the case of collinearity, Thompson and Borrello (1985) referred to a study (Borrello, 1984) investigating the personality correlates of test-wise skills. The researcher deliberately introduced collinearity into the study by measuring some constructs repetitively. This "multi-operationalization" is particularly appropriate in the social because our measures of abstract constructs are so fallible.

As shown in Table 1, an examination of the beta weights alone indicates that "Sensing" was the best predictor (β = -.310), followed by "Thinking" (β = .193) and "Extravert" (β = .148). However, an examination of the structure coefficients reveals an altogether different story. "Sensing" was most correlated with the Yhat variable (r_s = -.921), but "Intuition," the predictor variable with the second highest absolute-value structure coefficient (r_s = .783), had the third-most near-zero beta weight among the eight predictor variables (beta = -.059)!

Insert Table 1 About Here.

As Thompson and Borrello (1985) emphasized:

A slight fluctuation in a few bivariate correlation

> coefficients could radically alter a beta weight for a variable which is highly correlated with other predictors and which is only slightly more correlated with the criterion. If a variable's slight advantage in predictive power involves sampling or measurement error, then in subsequent studies the variable's beta weight will be dramatically closer to zero. Note, however, that the structure coefficients for the variables, "Intuition" (.783) and "Sensing" (-.921), suggest that both variables are noteworthy predictors of test-wiseness. (pp. 207-208)

Unlike beta weights, structure coefficients are unaffected by multicollinearity and thus provide the researcher with different information than beta weights. A predictor variable can have a near-zero beta weight and still be a good predictor of the criterion variable if the variance that the predictor *could* explain is arbitrarily assigned to another predictor variable.

Of course, as pointed out earlier, the examination of beta weights and structure coefficients is not an "either/or" question. Both sets of results can be consulted to answer different questions, as Thorndike (1978) pointed out. Indeed, it is only by examining both coefficients that intriguing data dynamics can be detected.

Examples from the Counseling Literature

Bowling (1993) reported that the Journal of Counseling

Psychology published 20 articles that used multiple regression analysis between January, 1990 and April, 1993. Of the 20 studies, only three reported structure coefficients in their results and only a few provided a correlation matrix that would allow an ambitious researcher to derive them post facto. My more recent review of articles published between January, 1996 and April, 1999 identified 22 articles using multiple regression. Clearly, the popularity of this statistical technique has not waned in one of the more prestigious counseling journals.

A Positive Example

The proper examination of both beta weights and structure coefficients was demonstrated in a multiple regression design by Longo, Lent, and Brown (1992) who examined the relationship between social-cognitive variables and motivation to participate in counseling. As shown in Table 2, an examination of beta weights alone indicates that "Outcome expectations" is only a moderately useful predictor of "Motivation" (β = .26), and that two predictors, "Self-efficacy" (β = .43) and "Problem severity" (β = .28) are assigned more credit for predicting variance in the criterion variable than "Motivation".

Insert Table 2 About Here.

However, an examination of the structure coefficients reveals that "Outcome expectations" has a very high structure coefficient (r_s = .90) and that this predictor alone accounts for 81% of the total variance accounted for by all five predictors. The discrepancy is due to high multicollinearity between "Outcome expectations" and three of the other four predictors, which were arbitrarily assigned more credit for capacity to explain variance in the criterion variable shared by the predictor variables.

In this study, the authors did not calculate the structure coefficients, but correctly examined the zero-order correlations between the predictor variables and took the high degree of multicollinearity into account when interrupting their results (Longo, Lent, & Brown, 1992): "Thus, despite the correlations between self-efficacy and outcome beliefs, the former explained somewhat more unique variance in motivation" (p. 450). As noted earlier, the zero-order correlations between predictor variables yield interpretations equivalent to those arising from structure coefficients, although the two sets of coefficients are expressed in a different metric (unless R = 1.0).

Example of Misinterpretation of Direct Effects

A recent article published in the American Journal of Family Therapy (Larson & Wilson, 1998) shows that, despite warnings to the contrary, leading counseling journals continue to publish studies that do not examine structure coefficients or zero-order correlations in addition to regression coefficients. Larson and Wilson (1998) studied the role of early family-of-origin influences on difficulties with later career decision-making. In the "Results" section of their report, they concluded that "Intimidation, trait anxiety, and class in college directly predicted career decision problems (betas = .09, .40, and -.16, respectively)" (p. 45).

Table 3 provides the beta weights as given in the study along with structure coefficients _not_ reported in the article but derived here through supplemental analysis. Had structure coefficients been interpreted in conjunction with regression coefficients, the researchers might have noticed that in relation to other predictors "Fusion" was substantially correlated with the Yhat variable, as shown by this variable having the second-largest absolute value among the eight structure coefficients. The near-zero beta weight for "Fusion" (-.04) can therefore be assumed to be a consequence of multicollinearity between the predictor variables in which the other predictor variables were arbitrarily assigned credit for the predictive power of "Fusion," not because "Fusion" is a useless predictor.

Insert Table 3 About Here.

Example of Misinterpretation of Indirect or "Suppressor" Effects

A study completed by Denham and Burton (1996) is an excellent example of failing to detect suppressor effects (Lancaster, 1999) in predictor variables by neglecting to consult structure coefficients in addition to beta weights. Suppressor variables are good predictors that directly predict little or no variance in the criterion variable, but which nonetheless _indirectly_ improve prediction by making the other predictors more effective (Horst, 1966).

In the study, the researchers concluded that the intervention (β = .666) and the interaction between the intervention and pretest

(β = -.696) were the only statistically significant contributors to teacher-rated competence, the criterion variable. Despite presenting zero-order correlations (which are related to structure coefficients) in the same table as the regression coefficients, the correlations between predictors were not taken into account when the results were interpreted. Had the researchers compared the beta weights with the structure coefficients, as shown in Table 4, it would have been apparent that the Intervention (β = .666) and the Intervention X Pretest (β = -.696) were nearly pure suppressors with large beta weights and near-zero structure coefficients (r_s = .04 and .02, respectively).

Insert Table 4 About Here.

In this case, these two predictor variables effectively removed extraneous variance or improved other predictors without directly accounting for variance in the criterion variable. In this instance, the researchers <u>erroneously</u> attributed explained variance to predictors that were almost completely uncorrelated with the criterion variable, but that made other predictor variables better by removing the bad variance in the other predictors!

<u>Summary</u>

It has been argued here that regression researchers frequently encounter collinear predictor variables, because this situation merely mirrors a reality in which predictors are often correlated, and because researchers frequently intentionally select collinear predictors in an effort to multi-operationalize fallible predictor variables. In these situations interpretations based solely on consultation of "standardized" regression weights can lead to grossly distorted conclusions. Examples from published literature were cited to illustrate these disturbing and fully avoidable occurrences of result misinterpretation.

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Table 1
Canonical Function and Standardized Regression (β) Coefficients and Zero-order Correlations and Structure Coefficients

Predictor Variable	Canonical Function Coefficients	β	r_{xy}	r_s
Extravert	-.371 X R =	-.148	-.051 / R =	-.128
Sensing	-.776 X R =	-.310	-.368 / R =	-.922
Thinking	-.484 X R =	-.193	-.192 / R =	-.481
Judging	-.131 X R =	-.052	-.117 / R =	-.293
Introvert	-.121 X R =	-.048	-.052 / R =	.130
Intuition	.149 X R =	.059	.313 / R =	.784
Feeling	-.275 X R =	-.110	.108 / R =	.271
Perceiving	-.215 X R =	-.086	-.109 / R =	.273

Note. These data were adapted from Thompson and Borrello (1984). Decimals were rounded here to three places. R = .399.

Table 2
Regression Coefficients, Zero-order Correlations, and Structure Coefficients For Longo, Lent and Brown (1992)

Predictor	β	r_{xy}	r_s
Gender	.13	.28	.41
Problem severity	.28	.31	.45
Counselor experience	-.06	-.08	-.12
Self-efficacy	.43	.53	.77
Outcome expectations	.26	.62	.90

Note. R^2 = .48; R = .69.

Table 3
Regression Results for a Study Investigating Family of Origin Influences on Career Decision Problems (Larson & Wilson, 1998)

Predictor	β	r_s
Gender	-.17	-.15
Age	.01	-.26
Income	.06	.11
Class	-.16	.34
Intimidation	.09	.43
Fusion	-.04	.51
Triangulation	.07	.31
Anxiety	.40	.85

Note. $R^2 = .22$; $R = .47$.

Table 4
Prediction of Post-test Teacher-Rated Social Competence (Denham & Burton, 1996)

Predictor	β	r_s
Intervention	.666	.04
Age	-.541	.42
Gender	.544	.48
Pretest	-.824	.78
Gender X Pretest	-.424	.80
Intervention X Pretest	-.696	.02
Age X Pretest	1.790	.78

Note. $R^2 = .291$; $R = .540$.

Figure 1

Venn Diagram for a Three Predictor Variable Regression Study